



## Accounting for dynamics of mean precipitation in drought projections: A case study of Brazil for the 2050 and 2070 periods

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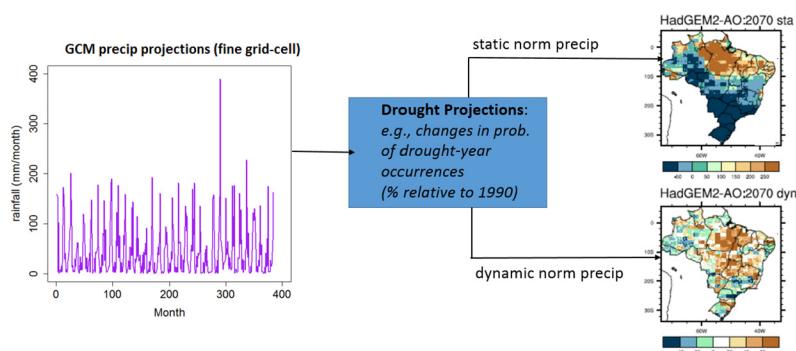
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### HIGHLIGHTS

- Challenges of drought projections to drought policy makers
- Applications of 'static' versus 'dynamic' normal condition applications in drought projections' construction
- Application of 'dynamic' normal condition gives more realistic projections of changes in droughts.
- Accounting for changes in normal precipitation conditions updates the perception of drought in a changing climate.

### GRAPHICAL ABSTRACT



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### ABSTRACT

Changes in drought around the globe are among the most daunting potential effects of climate change. However, changes in droughts are often not well distinguished from changes in aridity levels. As drought constitutes conditions of aridity, the projected declines in mean precipitation tend to override changes in drought. This results in projections of more dire changes in drought than ever. The overestimate of changes can be attributed to the use of 'static' normal precipitation in the derivation of drought events. The failure in distinguishing drought from aridity is a conceptual problem of concern, particularly to drought policymakers. Given that the key objective of drought policies is to determine drought conditions, which are rare and so protracted that they are beyond the scope of normal risk management, for interventions. The main objective of this Case Study of Brazil is to demonstrate the differences between projections of changes in drought based on 'static' and '30-year dynamic' precipitation normal conditions. First we demonstrate that the 'static' based projections suggest 4-fold changes in the probability of drought-year occurrences against changes by the dynamic normal precipitation. The 'static-normal mean precipitation' based projections tend to be monotonically increasing in magnitude, and were arguably considered unrealistic. Based on the '30-year dynamic' normal precipitation conditions, the 13-member GCM ensemble median projection estimates of changes for 2050 under rcp4.5<sup>1</sup> and rcp8.5<sup>2</sup> suggest: (i) Significant differences between changes associated with rcp4.5 and rcp8.5, and are more noticeable for droughts at long than short timescales in the 2070; (ii) Overall, the results demonstrate more realistic projections of changes in drought characteristics over Brazil than previous projections based on 'static' normal precipitation conditions. However, the

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<sup>1</sup> rcp4.5: pathway of greenhouse gas emissions where total radiative forcing is stabilised (at  $4.5 \text{ W m}^{-2}$ ) shortly after 2100, without overshooting the long-run radiative forcing target level.

<sup>2</sup> rcp8.5: pathway of greenhouse gas emissions which, assumes high population and slow income growth with modest rates of technological change and energy intensity improvements, leading to high energy demand and greenhouse gases emissions in absence of climate change policies.



uncertainty of response of droughts to climate change in CMIP5 simulations is still large, regardless of GCMs selection and translation processes undertaken.

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## 1. Introduction

Expansion of atmospheric circulation pattern known as the Hadley Cell (in which warm air in the tropics rises, loses moisture to tropical thunderstorms, and descends in the subtropics as dry air) is associated with climate change/global warming (Seidel et al., 2008). As jet streams continue to shift to higher latitudes, and storm patterns shift along with them, semi-arid and desert areas are expected to expand. A decline in precipitation conditions, therefore, is projected over the subtropics, whereas areas in high-latitudes are expected to get wetter. Evidently, there has been a general increase in precipitation over high latitudes and near the equator, and a decrease in the sub tropics since 1950 (Knutti and Sedláček, 2013; Dai, 2011a, 2011b; Gao and Giorgi, 2008; IPCC, 2013).

In drier regions, evapotranspiration may exacerbate the impacts of drought—leading to below-normal levels of rivers, lakes, and groundwater (hydrological drought impact), and lack of enough soil moisture in agricultural areas (agricultural drought impact). However, climate change can worsen drought in multiple ways even without reduction in mean precipitation. The drought concept is much more than just a reduction in precipitation. For example, unprecedented nature of recent California droughts has been attributed to the loss of Arctic ice and dramatic changes in jet streams (Sewall and Sloan, 2004). More importantly, that attribution serves as a warning that climate change can have small effects in one location that propagate through the system to have big effects elsewhere. Indeed, as the climate changes, the effects on drought might vary a lot from one region to another, and it may be hard to predict where the effects will be felt most.

As drought constitutes conditions of aridity, projected decline in mean precipitation often tends to obscure or override projections of changes in drought characteristics. In principle, drought is a temporary phenomenon, different from aridity which is rather permanent (Mpelasoka et al., 2018). However, most studies do not distinguish between drought and decline in mean precipitation, and as a result they often tend to project more dire changes in drought characteristics than ever. For example, Burke et al. (2006) projected the areal-extent of extreme droughts to increase from current 1% of the global land surface to 30% by the end 21st century. Similarly, Dai et al. (2004) associated the observed increase in dry global land areas since 1970s with unprecedented droughts. Nevertheless, Dai (2011a, 2011b) acknowledged that the current indices (e.g. Palmer Drought Severity Index) may not capture the range of conditions that future climate may produce.

Intuitively, the perception of drought for future periods based on 'static normal precipitation' conditions across the entire domain of the precipitation time series may not be realistic. For example, the mean value of precipitation in the present day climate would no longer be regarded as the normative value for design purposes or planning policies relevant in future periods. Analogously, WMO recommends the use of operational normal values in addition to the classic 30-year normal values in drought prediction (Trewin, 2007). The key objective of drought policies is to distinguish drought conditions that are rare and so protracted that they are beyond the scope of normal risk management (Mpelasoka et al., 2008; Wilhite et al., 2014; Wilhite et al., 2000). For example, in Australia this forms the basis for subsequent governmental drought relief restricted only to areas declared to be under drought as 'exceptional circumstances'. Indeed, the tendency of not differentiating droughts from aridity is a conceptual problem, particularly to drought policymakers.

To address this problem we use '30-year dynamic' normal precipitation conditions by deriving projections of changes in drought characteristics in a Case Study of Brazil. First, we demonstrate the differences

between projections of change in drought occurrences based on 'static' normal precipitation conditions (as in previous studies) and those derived with '30-year dynamic' normal conditions. The use of 'dynamic' normal conditions potentially accounts for changes in normal precipitation, and in addition, it is logically consistent with the drought perception relevant to different future periods. The transient 'GCM world' monthly precipitation from 25 CMIP5 global climate models (GCMs) are translated to the 'real world' on a 0.25° grid over Brazil. After model evaluation and selection processes, precipitation series from 13 GCMs are transformed into Standardized Precipitation Index (SPI) using updated normal precipitation conditions. Projections of changes in the probability of drought-year occurrences, drought duration and areal-extent (50th and 90th percentiles) under rcp4.5 and rcp8.5 relative to 1990 (1975–2005) are estimated by 13-member GCM ensemble medians for the 2050 (2035–2065) and 2070 (2055–2085) periods.

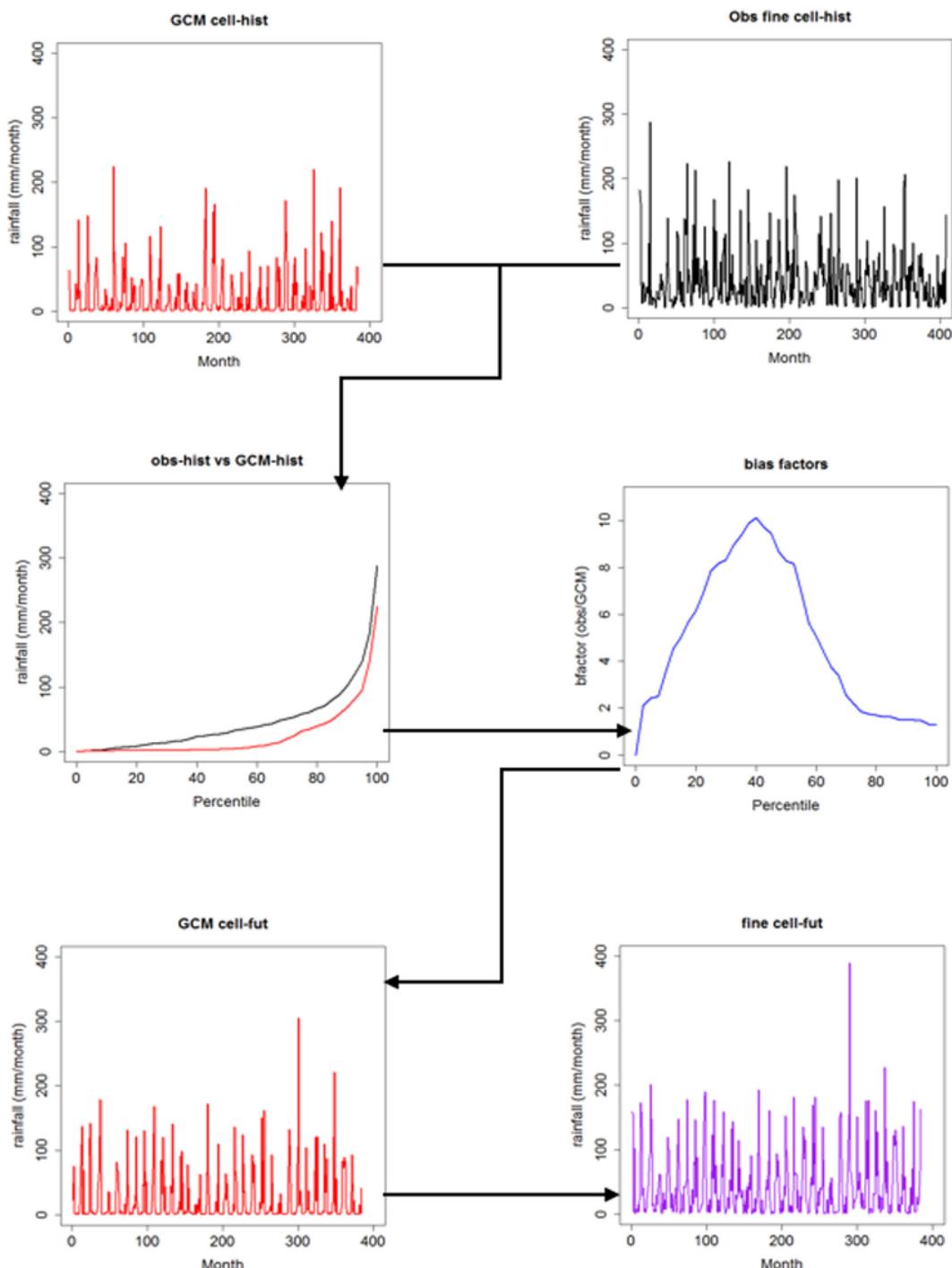
## 2. Data and methodology

Future precipitation changes cannot be simply extrapolated from past records and in addition, they depend on future greenhouse gases concentration pathways. The best tools for climate change projections are the general circulation models also known as global climate models (GCMs). These are the most 'complete' models of the climate system, capable of solving the fundamental physical laws which govern the behaviour of the atmosphere, ocean and land surface. Confidence in the

**Table 1**

List of CMIP5 GCMs from which precipitation and SST data were drawn. Tabulated are the grid resolutions, (i.e. distance between adjacent grid points in degrees). In case of the atmospheric grid and its latitude, the tabulated resolution is only valid for the equatorial region. For higher latitudes deviations may occur. Ocean models have their own, finer grid. If two values are given for the latitude resolution of the ocean grid, resolution is not constant. The first value is that for the equator while the second for the poles (maximum for the two poles if different). In case of rotated poles the resolutions for the rotated coordinates lon and rlat are tabulated. lat(i,j) and lon(i,j) denote latitudes and longitudes defined with two indices i and j. In this case the resolution cannot simply be read out. Source: ENES (2017).

Model	Atmospheric Grid		Ocean Grid	
	Latitude	Longitude	Latitude	Longitude
ACCESS1-0	1.25	1.875	lat(i,j)	lon(i,j)
ACCESS1-3	1.25	1.875	lat(i,j)	lon(i,j)
Bcc-csm1.1	2.7906	2.8125	0.3333, 1	1
CCSM4	0.9424	1.25	lat(i,j)	lon(i,j)
CNRM-CM5	1.4008	1.40625	lat(i,j)	lon(i,j)
CSIRO-Mk3.6.0	1.8653	1.875	0.9327, 0.9457	1.875
FGOALS-g2	2.7906	2.8125	0.5, 1	1
FIO-ESM	1.1	0.6	0.5, 1	1
GFDL-CM3	2	2.5	0.3344, 1	1
GFDL-ESM2G	2.0225	2	0.375, 0.5	1
GFDL-ESM2M	2.0225	2.5	0.3344, 1	1
GISS-E2-H	2	2.5	1	1
GISS-E2-R	2	2.5	1	1.25
HadGEM2-AO	1.25	1.875	0.3396, 1	1
INM-CM4	1.5	2	0.5	1
IPSL-CM5A-LR	1.8947	3.75	lat(i,j)	lon(i,j)
IPSL-CM5A-MR	1.2676	2.5	lat(i,j)	lon(i,j)
MIROC-ESM	2.7906	2.8125	0.5582, 1.7111	1.40625
MIROC-ESM-CHEM	2.7906	2.8125	0.5582, 1.7111	1.40625
MIROC5	1.4008	1.40625	0.5, 0.5	1.40625
MPI-ESM-LR	1.8653	1.875	Orthogonal curvilinear coordinates	
MPI-ESM-MR	1.8653	1.875	lat(i,j) and lon(i,j)	
MRI-CGCM3	1.12148	1.125	0.5, 0.5	1
NorESM1-M	1.8947	2.5	lat(i,j)	lon(i,j)
NorESM1-ME	1.8947	2.5	lat(i,j)	lon(i,j)



**Fig. 1.** Illustration of Translation method through three steps: (1) the observed and GCM historical precipitation time series are aligned for the comparison of the distributions in (2) to determine the bias factors. The bias factors are then applied percentile-wise to the GCM future precipitation series in (3) to produce precipitation series on a relatively fine grid-cell.

use of GCMs for projections comes from their ability to represent important features of the current and past climate (Randall et al., 2007).

### 2.1. Data

The observed (1980–2013) and simulated (1974–2005) historical monthly precipitation time series (hereafter referred to as the “present day”) were used in conjunction with simulated precipitation series for 2035–2065 (2050) and 2055–2085 (2070) periods. The observed data were based on daily precipitation series on a  $0.25^\circ \times 0.25^\circ$ , latitude x longitude grid over Brazil (Xavier et al., 2016). Whereas, the simulated data

were drawn from outputs of 25 GCMs. The models (listed in Table 1) participated in the Coupled Model Inter-comparison Project Phase 5 (CMIP5), <https://www.wcrp-climate.org/wgcm-cmip/wgcm-cmip5>. For future periods, two realizations of emission pathway scenarios that include rcp4.5 (Thomson et al., 2011) and rcp8.5 (Riahi et al., 2011), used in the AR5 IPCC Report,<sup>3</sup> were considered. Similarly, the sea surface

<sup>3</sup> AR5 IPCC Report: The Fifth Assessment Report by the Intergovernmental Panel on Climate Change that provides a clear and up to date view of the current state of scientific knowledge relevant to climate change.

temperature (SST) data were drawn from the NCEP/NCAR Reanalysis (Kalnay et al., 1996), and the CMIP5 GCMs' simulations.

## 2.2. Methodology

Four key aspects of analysis were undertaken, i.e., (i) GCM precipitation evaluation and model selection, (ii) translation of 'GCM world' information to the "real world", (iii) identification of drought events, and subsequently (iv) quantification of drought characteristics.

### 2.2.1. Evaluation of GCM precipitation

The simulated historical precipitation from 25 GCMs were evaluated against observed precipitation on a  $0.25^\circ \times 0.25^\circ$  grid over Brazil for the skill in temporal distributions. The Kolmogorov-Smirnov test (Conover, 1972), was used to quantify the similarity of temporal distributions between the model and the observed precipitation at each grid-cell. This test is a nonparametric goodness-of-fit, where a statistic metric "D" (hereafter referred to as K-S D) is the maximum distance between the two cumulative functions of distributions. Thus "D" ranges from 0 to 1, and in

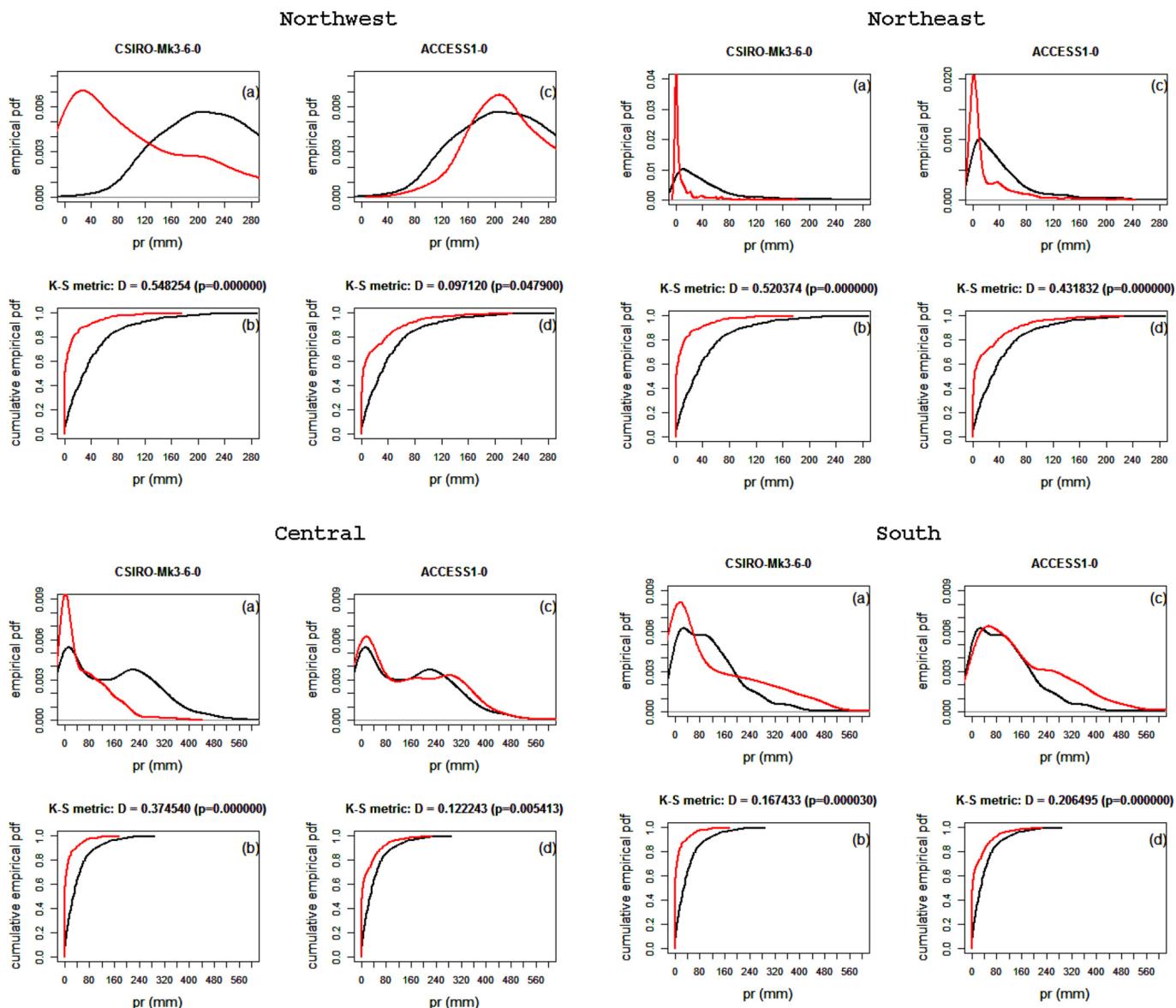
this application, 0 indicates a perfect match of the GCM derived temporal distribution with the observed, whereas 1 implies a complete mismatch.

### 2.2.2. Translation method

The modified future precipitation series are generated using a translation method (kind of bias correction extended to each individual values of the series), as illustrated in Fig. 1. This is a distribution mapping technique, which establishes relationships percentile-wise between the historical GCM-scale precipitation and the observed on a relatively fine grid (e.g.,  $0.25^\circ \times 0.25^\circ$ ) across the study domain. The concept of precipitation series translation method has been shown to be skillful in different settings, e.g., in Mpelasoka and Chiew (2009), Wood et al. (2004), and Maurer and Hidalgo (2008).

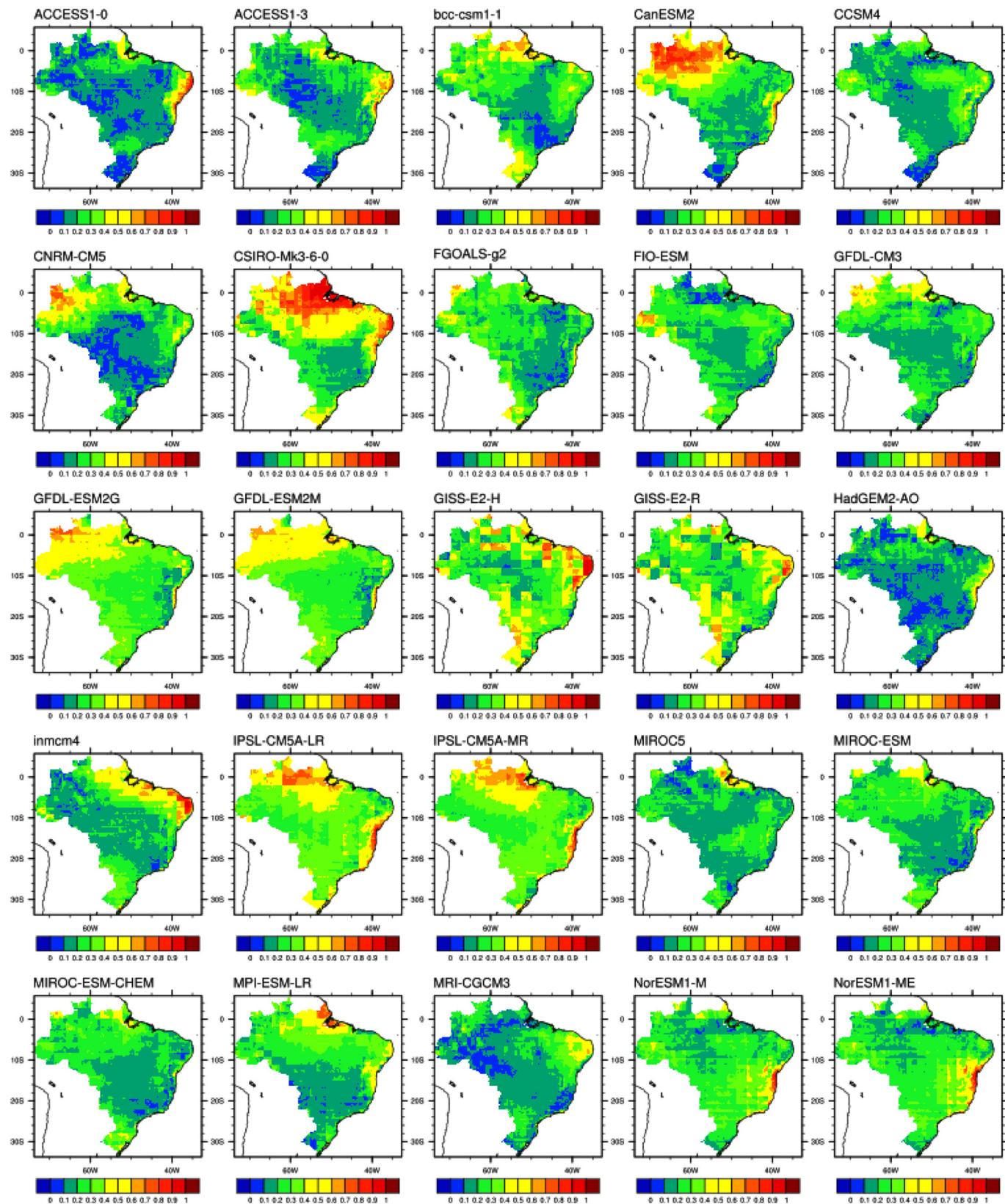
## 2.3. Identification of drought events

The identification of drought events was based on Standardized Precipitation Index (SPI) developed by McKee et al. (1993) and recommended by the World Meteorological Organization for monitoring of



**Fig. 2.** Model skill for ACCESS1-0 versus CSIRO-Mk3.6.0 GCMs over selected grid-cells that represent the northwestern, northeastern, central and southern sectors of Brazil. Comparisons of modelled (red) and observed (black) empirical probability density functions (pdfs) are shown in panels (a) and (c), and the similarity quantified by the K-S D values in panels (b) and (d).

### Kolmogorov-Smirnov 'D' for 25 GCMs



**Fig. 3.** Spatial variation of GCMs' performance as measured by the K-S "D" statistic across Brazil. D value 0 indicates a perfect match of the GCM derived temporal distribution with the observed, whereas 1 implies a complete mismatch.

dry spells (WMO, 2012). It is versatile, and its advantages include; e.g., requirement of only monthly precipitation, comparable across regions with markedly different climates, and can determine the rarity of a drought event (e.g., Awange et al., 2016 and Mpelasoka et al., 2018).

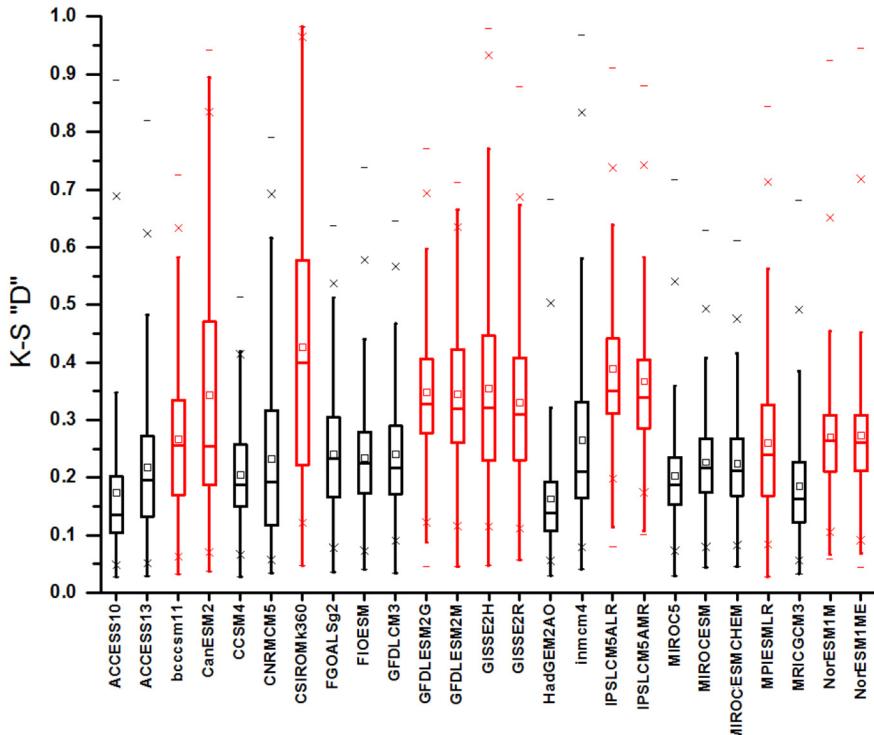
Moreover, the SPI is designed to quantify the precipitation deficit for multiple timescales. These timescales reflect the impacts of droughts on the availability of the different water resources. For example, soil moisture conditions respond to precipitation anomalies on a relatively short timescale, while groundwater, streamflow and reservoir storage reflect precipitation anomalies at long timescales. In this study, the focus is on the 6-month and 24-month timescales, hereafter referred to as short- and long-timescales, respectively. More importantly, to account for the projected climatology dynamics, the precipitation anomalies in the SPI calculations are based on updated normal precipitation conditions for each future period. Subsequently, drought events are revealed by inspection of time intervals where SPI values are less than negative 0.9 for at least 3 consecutively months (Mpelasoka et al., 2018).

#### 2.4. Modeling the probability of drought-year occurrences

The probability of drought-year occurrences was modelled on *Beta* distribution. The model has been successfully used elsewhere, e.g., in Mpelasoka et al. (2018). This is a natural conjugate prior distribution in the Bayesian sense (i.e., evidence about the true state) and represents all possible values of unknown probabilities. If these probabilities constitute a continuous random variable  $x$  that follow a *Beta* distribution with parameters  $\alpha$  and  $\beta$ , where  $0 < \alpha < 1$  and  $0 < \beta < 1$ ;  $\alpha$  and  $\beta$  are chosen to reflect any existing belief, then the probability density function of  $x$  takes the form of Eq. (1) (Evans et al., 2000),

$$f(x|\alpha, \beta) = \frac{x^{\alpha-1}(1-x)^{\beta-1}}{B(\alpha, \beta)}, \quad 0 < x < 1, \quad (1)$$

where  $B(\alpha, \beta) = \frac{\Gamma(\alpha)\Gamma(\beta)}{\Gamma(\alpha+\beta)}$  is the beta function (normalizing constant) and



**Fig. 4.** Summary of GCMs' spatial distribution of K-S D statistic across Brazil by the box-and-whisker plots portraying the 1st and 2nd quantiles (rectangle box); the median and mean (horizontal line/small square inside the box); and the whiskers indicating variability outside the upper and lower quantiles.

where  $\Gamma(\alpha)$  is the gamma function

$$\Gamma(\alpha) = \int_0^\infty x^{\alpha-1} e^{-x} dx. \quad (2)$$

The mean  $\mu$  and variance  $\sigma^2$  of the Beta random variable  $x$  are

$$\mu = \frac{\alpha}{\alpha + \beta} \in (0, 1), \quad (3)$$

and

$$\sigma^2 = \frac{\alpha\beta}{(\alpha + \beta)^2(\alpha + \beta + 1)} = \frac{\mu(1-\mu)}{\alpha + \beta + 1} < \frac{\mu(1-\mu)}{1} \in (0, 0.5^2), \quad (4)$$

respectively.

Solving for  $\alpha$  and  $\beta$  using Eqs. (3) and (4) shows that:

$$\alpha = \left( \frac{1-\mu}{\sigma^2} - \frac{1}{\mu} \right) \mu^2 \quad (5)$$

and

$$\beta = \alpha \left( \frac{1}{\mu} - 1 \right) \quad (6)$$

We model transient probability of drought-year occurrences, as more information become available. Whereas the mathematics for proving the updating procedure is a bit involved (Evans et al., 2000), the operation is very simple. If  $h$  and  $m$  are the numbers of hits and misses of drought-year occurrences respectively, at the  $i$ th time step, the *Beta* distribution takes the form of Eq. (7).

$$\text{Beta}(\alpha_i, \beta_i) = \text{Beta}(\alpha_{i-1} + h, \beta_{i-1} + m) \quad (7)$$

For each grid-cell, the initial parameters  $\alpha_0$  and  $\beta_0$  were estimates from  $\mu_0$  as the long-term probability (i.e., proportion count of years in

drought to the total number of years). First, the standard deviation ( $\sigma$ ) estimate is based on the *empirical rule*, where 95% of the values lie within  $\mu \pm 2\sigma$  (assuming normally distributed variables) (Pukelsheim, 1994; Wheeler and Chambers, 1992). For example, for  $\mu$  equal to 0.35 (i.e., between 0.3 and 0.4),  $\sigma$  is calculated as  $(0.025 * (0.4-0.3) / 4)$ . Once  $\sigma$  is known, then  $\alpha_0$  and  $\beta_0$  can be determined from Eqs. (5) and (6).

### 3. Results

#### 3.1. GCM precipitation evaluation and model selection

There are variations in the skill of GCMs precipitation simulations as quantified by the K-S D statistic, across Brazil and among models. For example, Fig. 2 compares the model skill for ACCESS1-0 and

CSIRO-Mk3.6.0 GCMs over selected grid-cells. For sector representative grid-cell, the visual comparisons of modelled and observed empirical probability density functions (pdfs) are shown in panels (a) and (c), and the similarity quantified by the K-S D values in panels b and d. For the northwestern sector, ACCESS1-0 has better skill than CSIRO-Mk3.6.0 with K-S D values of 0.09 and 0.54, respectively. Similarly, over the central areas ACCESS1-0 (K-S D = 0.12) performs better than CSIRO-Mk3.6.0 (D = 0.37). However, both ACCESS1-0 and CSIRO-Mk3.6.0 exhibit similar skills over the southern (K-S D = 0.20/0.16, fair) and northeastern (K-S D = 0.43/0.52, poor). As shown in Fig. 3, the majority of the 25 models perform fairly well over western, central and southern Brazil.

The overall model performances in terms of precipitation simulation across the country are summarized in Fig. 4. The models

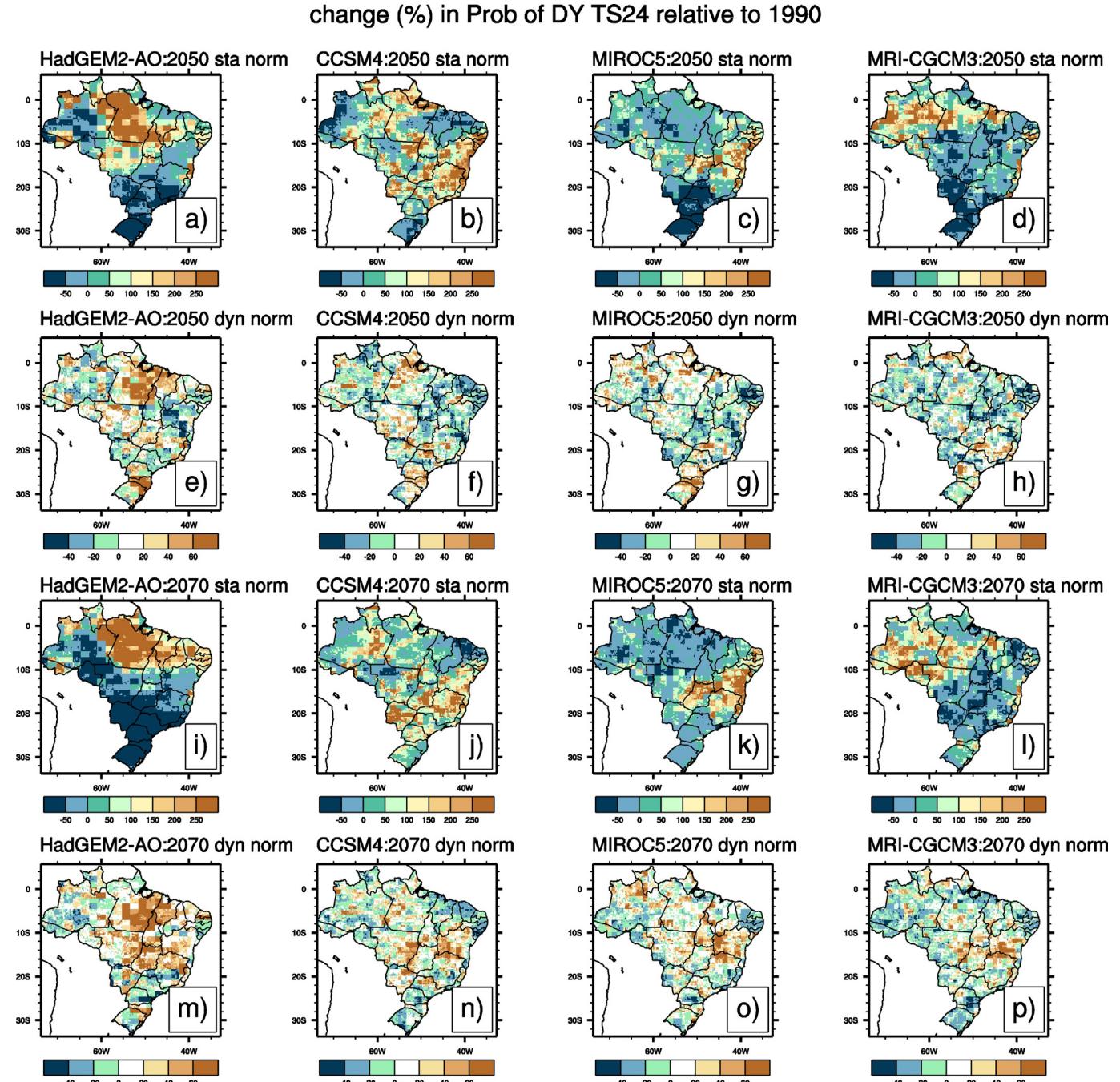
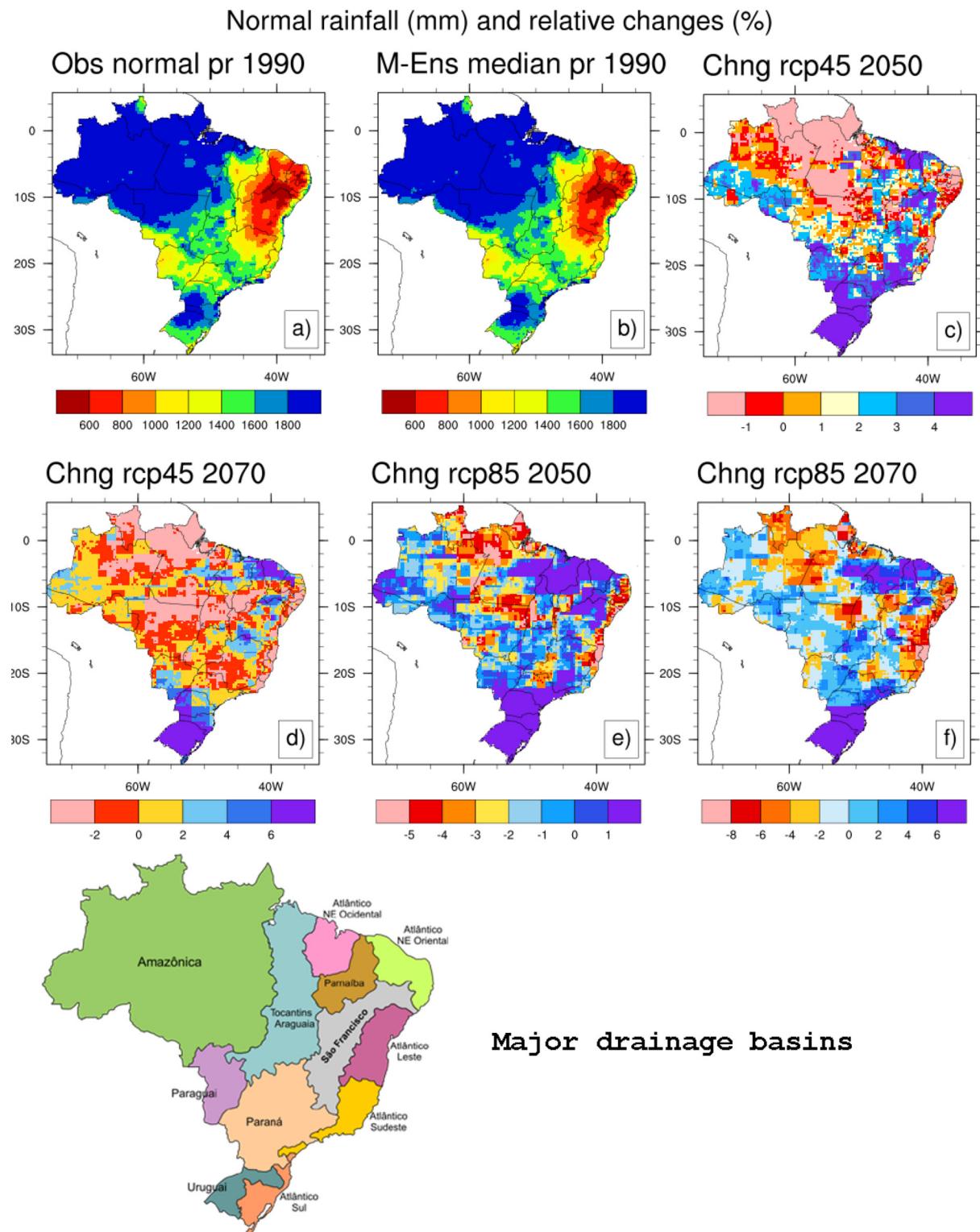


Fig. 5. Projected changes in probability of drought-year occurrences at 24-month timescales based on static (sta) and dynamic (dyn) normal precipitation conditions shown in panels (a) through (d) and (e) through (h) respectively for 2050; panels (i) through (l) and (m) through (p) for 2070 derived from HadGEM2-AO, CCSM4, MIROC5 and MRI-CGCM3 GCMs simulations under rcp4.5.

shown in black demonstrated more acceptable skill than others. Therefore, only 13 GCMs were retained for the projections evaluation of drought characteristics: ACCESS1-0, ACCESS1-3, CCSM4, CNRM-CM5, FGOALS-g2, FIO-ESM, GFDL-CM3, HadGEM2-AO, inm-cm4, MIROC5, MIROC-ESM, MIROC-ESM-CHEM, and MRI-CGCM3.

### 3.2. Projections of changes in droughts based on 'static' versus '30-year dynamic'- normal precipitation

Projected changes in drought characteristics show remarkable differences between droughts derived using static-normal precipitation and those based on '30-year dynamic' normal precipitation. Particularly,

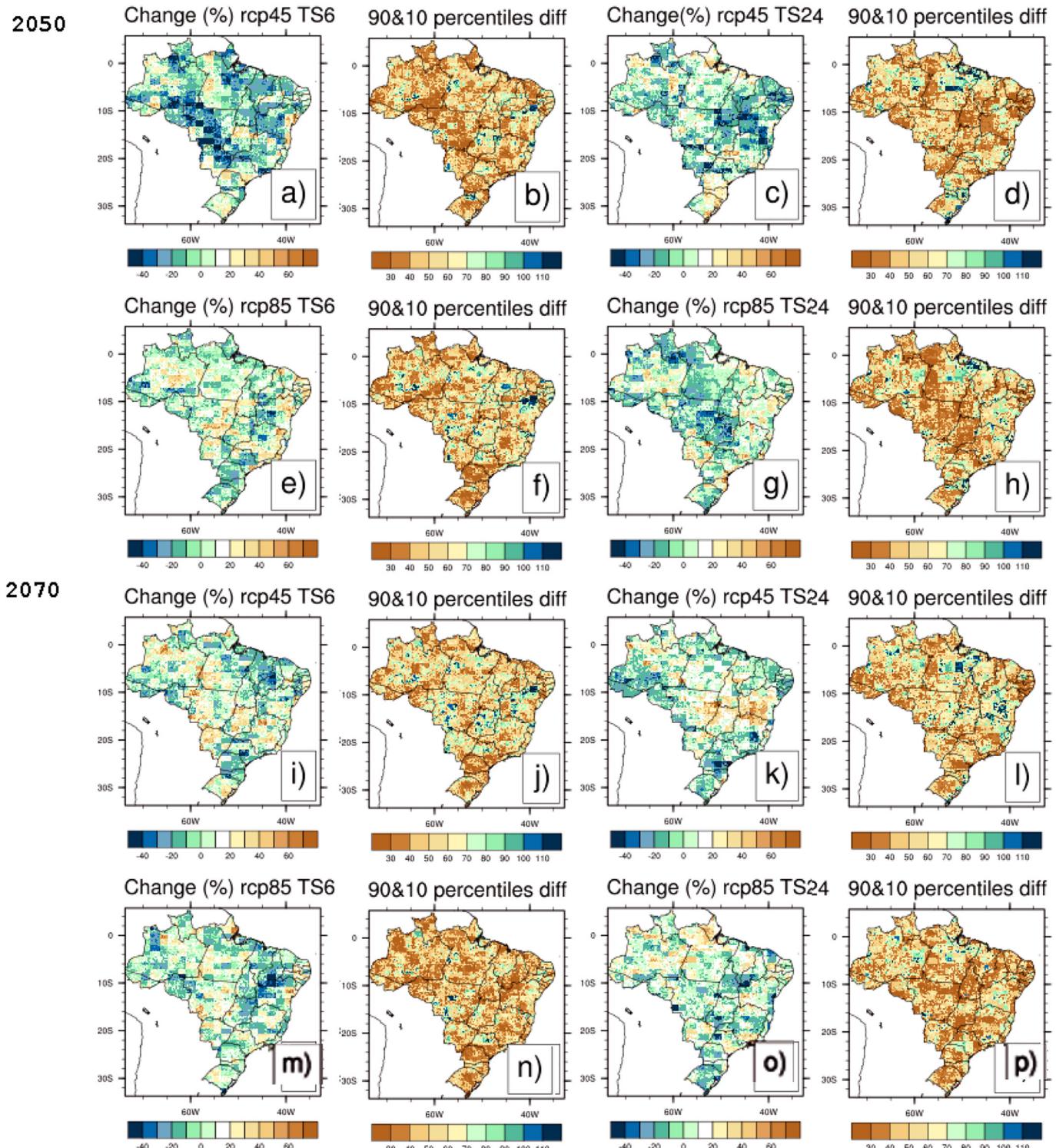


**Fig. 6.** Comparison of (a) Mean observed precipitation and (b) 13 GCM ensemble median translated precipitation (mm); projections of changes in precipitation (% relative to the 1990 normal) associated with rcp4.5 for (c) 2050 and (d) 2070; and associated with rcp8.5 for (e) 2050 and (f) 2070. In addition, below is the major drainage basins for easy reference.

in the probability of drought-year occurrences. All 13 GCMs show over 4-fold changes for rcp4.5 and rcp8.5 emission scenarios, at both short and long timescales. This is as demonstrated in Fig. 5 for the 24-month timescale drought-year occurrences, derived from HadGEM2-

AO, CCSM4, MIROC5 and MRI-CGCM3 models under rcp4.5 (panels **a** through **d**; **j** through **l**) versus changes by the dynamic (panels **e** through **h**; **m** through **p**) normal precipitation. More importantly, the static normal precipitation based projections tend to show monotonic

### Ensemble median DY prob relative changes & model diff. (%)



**Fig. 7.** Thirteen member ensemble median changes in the probability of drought-year occurrences relative to 1990 and the difference between the 10th and 90th percentiles for the 2050 period under rcp4.5, for drought 6-month (panels **a** and **b**) and 24-month timescales (panels **c** and **d**); under rcp8.5, for drought 6-month (panels **e** and **f**) and 24-month timescales (panels **g** and **h**). Similarly for the period 2070 under rcp4.5, for drought 6-month (panels **i** and **j**) and 24-month timescales (panels **k** and **l**); under rcp8.5, for drought 6-month (panels **m** and **n**) and 24-month timescales (panels **o** and **p**).

**Table 2**

Proportions of Brazil land area (%) under projected increase ( $>5\%$ ) and decrease ( $<-5\%$ ) in probability of drought-year occurrences for the 2050 and 2070 periods for the realizations of rcp4.5 and rcp8.5 scenarios of greenhouse emission pathways.

Projected changes in probability of drought-year occurrences	2050				2070			
	rcp4.5		rcp8.5		rcp4.5		rcp8.5	
	DTS6	DTS24	DTS6	DTS24	DTS6	DTS24	DTS6	DTS24
Increase	13	72	35	72	12	24	28	66
Decrease	78	14	36	13	71	45	55	10

increases in the magnitude of changes over time (e.g., between 2050 and 2070).

### 3.3. Combined insights from 'translation action' and 'GCM projections'

A spatial detail in the precipitation change signal, at the observation grid resolution is shown in Fig. 6. Under the realization of rcp4.5 scenario, changes in mean precipitation for 2050 and 2070 range from  $-1$  to  $+4\%$  and  $-2$  to  $+6\%$ , respectively. Increases are expected mainly over the western and southern, and to a less extent over the Atlantico NE Ocidental, parts of Pamaiba and Sao Francisco basins, and decreases elsewhere for the 2050 period. In the 2070 period, the decreases of up to  $2\%$  widespread across the country, except for the far southern parts, and parts of Atlantico NE Ocidental and northern Pamaiba basins, where increases of up to  $6\%$  are expected.

Under the realization of rcp8.5 scenario, changes range between  $-5$  to  $+1\%$  in the 2050 period, and between  $-8$  to  $+6\%$ . The decreases are mainly for the eastern Amazonica, northern Parana and southern Sao Francisco. In the 2070 period the changes range between  $-8$  to  $+6\%$ , and the increase is mainly to the southwest Amazonica and southern sector of the country.

### 3.4. Ensemble projections in drought characteristics

Projections of changes in key drought characteristics that include probability of drought-year occurrences, drought duration and areal-extent are reported in form of a 13 member GCM median ensemble of changes. As demonstrated in Section 3.2, there are remarkable differences in GCM results, therefore the ensemble median best summarises the projected spread and the amount of spread the GCMs related uncertainty in the projections.

#### 3.4.1. Probability of drought-year occurrences

Under the realization of rcp4.5, Fig. 7 shows changes in probability of drought-year occurrences for droughts at 6- and 24-month timescale exhibit changes between  $-40$  to  $+40\%$  in the 2050 period. The decreases are more widespread than increases, particularly over southwest and the eastern areas, while the increases are mainly to the south of the country, and isolated patches in the north (panels a and c). The range of differences in between the 10th and 90th percentiles (panels b and d) is on the average about 50 and 30% for the 6- and 24-month timescale droughts, respectively. Under the rcp8.5, changes for the 6-month timescale show widespread decreases of 10 to 20% (panel e). Increases of up to 20% are shown mainly over the Amazonica, central and eastern areas, while decreases of up to  $-40\%$  are shown elsewhere for the 24-month timescale droughts. However, the increases are limited to about 10% (panel g).

The projected changes for 2070, exhibit widespread decreases in probability of drought-year occurrences of up to 30% for droughts at 6-month timescale. The decrease is more pronounced over the western Amazonica, the Atlantico NE Ocidental and Parana basins (panels i). Whereas isolated patches of increases of about 20% in the probability of drought years are noticeable elsewhere. However, there is no much contrast between the patterns of changes associated with rcp4.5 and rcp8.5, for droughts at the 6-month timescale (panels i and m).

In Table 2, the proportions of Brazil land area under projected increase ( $>5\%$ ) and decrease ( $<-5\%$ ) in probability of drought-year occurrences, show decreases in probability of occurrences of short-timescale drought-years for around 80% of the area for the 2050. On the contrary, increases over the about the same proportion of the area as projected for the same period. However, there are reductions in the proportions of the area with projected decreases and also increases in the 2070 period.

#### 3.4.2. Changes in drought duration

Under rcp4.5, a general decrease in drought duration is projected over Brazil for the 2050 period, for droughts at both short and long timescales. As shown in Fig. 8 (panels a and c), decreases of 5 to 10% are widespread across the country. Only isolated patches of increases of about 30% in the central and small portion of the southern areas for the 6-month timescale droughts, extending to the northwest for the 24-month timescale droughts. Under rcp8.5, the patches showing increased duration by about 30% become more visible, but still decreases of up to  $-15\%$  are dominant for droughts at 6-month timescales (panel e).

For the 2070 period, under rcp4.5 a general decrease of 5 to 10% is projected for the 6-month timescale droughts (panel i); and widespread increased duration for the droughts at 24-month timescale by up to 30% (panel k). On the other hand, the differences between the 10th and 90th percentile changes range from 20 to 120% (panels b, d, f, and h, j, l, n and p).

Table 3 summarises the proportions of Brazil land area (%) under projected increase ( $>5\%$ ) and decrease ( $<-5\%$ ) in drought 50<sup>th</sup> and 90<sup>th</sup> duration percentiles for the 2050 and 2070 periods. Generally, increases in both duration categories are projected for most areas (proportions of up to 73%), particularly the 90th percentile duration category. Nevertheless, decreases in average duration are projected for over 60% of the area for 2050 short-timescale droughts under rcp8.5.

#### 3.4.3. Changes in drought areal-extent

As summarized in Table 4, the projections for the 2050 period associated with rcp4.5 are decreases of up to 3% in median drought areal-extent at short timescales. Whereas at long timescales increases of about 11% are projected for the 90th percentile. On the other hand, little changes ( $-0.04$  to  $1.6\%$ ) are associated with rcp8.5 for the median drought areal-extent, and an increases of about 5% in the 90th drought areal-extent for droughts at both short and long timescales. Whereas for the 2070 period more decreases (up to 11%) are projected for the median areal-extent and only slight increases for the 90th percentile areal-extent at all drought timescales.

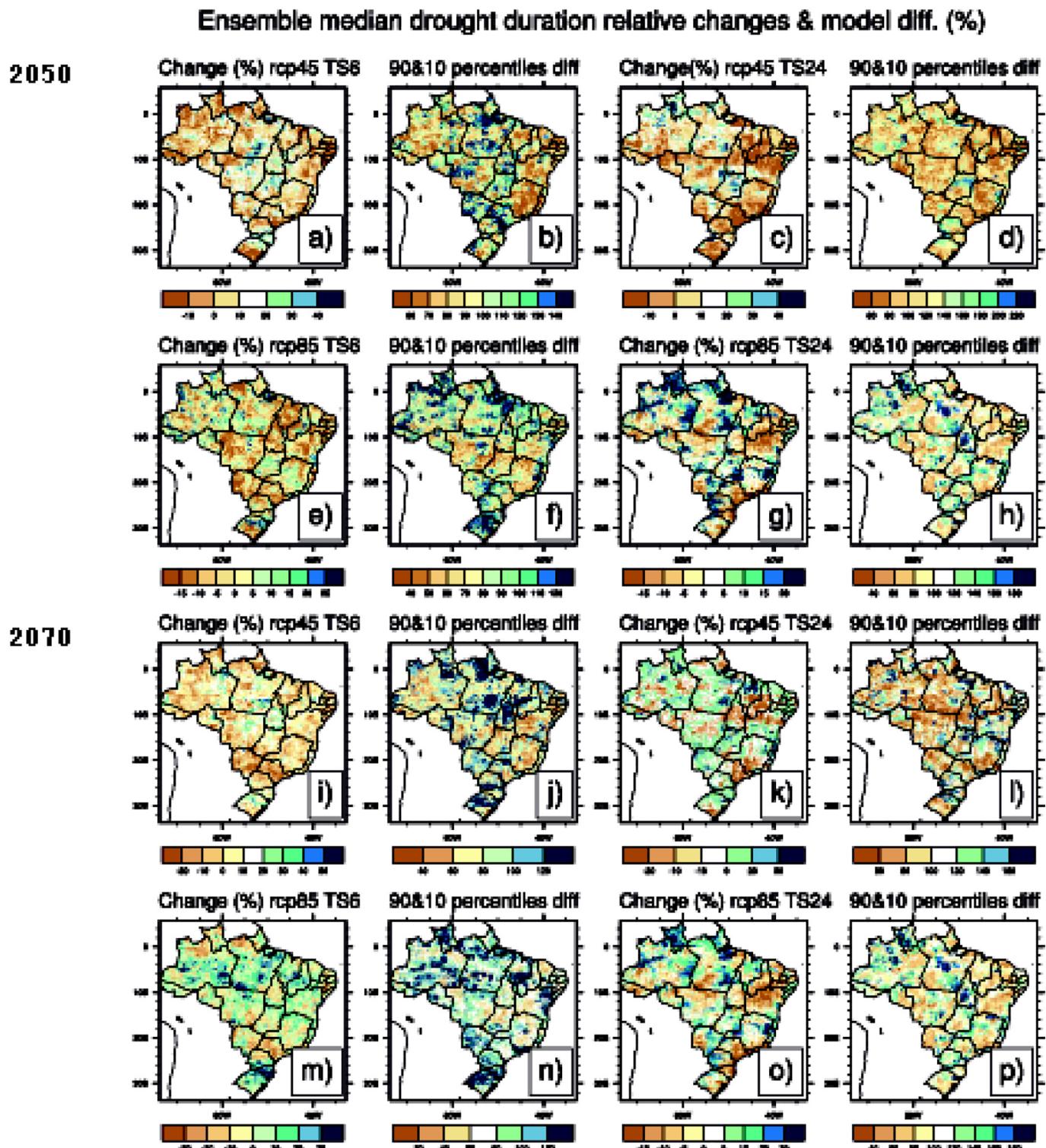
## 4. Discussion

Generally, the synthesis of model evaluation is to help rate confidence in GCM simulations. This can add to the overall confidence assessment of future projections for the region. The GCM selection provides a subset that is considered representative of the range of future precipitation simulations. Nevertheless, the selection process also can provide the challenge and opportunity to eliminate any models which were found unsatisfactory in their simulations. The exclusion of GCMs has been explored in a number of studies (Watterson and Whetton, 2011; Sexton et al., 2012). Critically, the elimination of some GCMs may narrow the range of uncertainty represented by the remaining models. While this is often considered desirable given the policy challenges in responding to projections with large uncertainty ranges, provision of a falsely narrow range of projections may lead to over confidence and mal-adaptation. With this in mind, we used a generous threshold (K-S D statistic  $\leq 0.2$ ) as a selection criteria such that only the 'worst' GCMs were eliminated.

The projections derived after model selection and translation processes, provide an informal 'ensemble' which has additional spatial detail in the precipitation change signal. This result is consistent across the

three different drought statistics. The bias corrected drought projections also generally have slightly more agreement (smaller range of future changes) across the GCMs compared to the raw projections, which is a promising result for attempting to reduce model structural uncertainty (Burke and Brown, 2008). In addition, the translation (percentile-wise bias correction) method has advantage over other

simple scaling methods commonly used in impact studies. The translation method conserves climate change dynamics as simulated in GCM transient precipitation time series (Mpelasoka and Chiew, 2009). This is crucial in the analysis of extreme events such as droughts, which are expected to dominate as climate change eventuates (IPCC, 2015).



**Fig. 8.** Thirteen GCM member ensemble median changes (%) in drought duration relative to 1990 and the difference between the 10th and 90th percentiles for the 2050 period under rcp4.5, for drought 6-month (panels a and b) and 24-month timescales (panels c and d); under rcp8.5, for drought 6-month (panels e and f) and 24-month timescales (panels g and h). Similarly for the period 2070 under rcp4.5, for drought 6-month (panels i and j) and 24-month timescales (panels k and l); under rcp8.5, for drought 6-month (panels m and n) and 24-month timescales (panels o and p).

**Table 3**

Proportions of Brazil land area (%) under projected increase ( $>5\%$ ) and decrease ( $<-5\%$ ) in drought 50th/90th duration percentiles for the 2050 and 2070 periods for the realizations of rcp4.5 and rcp8.5 scenarios of greenhouse gases emission pathways.

Projected change in drought duration	2050				2070			
	rcp4.5		rcp8.5		rcp4.5		rcp8.5	
	DTS6	DTS24	DTS6	DTS24	DTS6	DTS24	DTS6	DTS24
Increase	26/73	68/55	11/68	70/55	11/56	42/52	13/60	54/16
Decrease	11/13	18/29	63/16	17/29	47/16	25/32	47/17	39/30

As acknowledged that drought indices in their current form may not capture the range of future climate conditions (Dai, 2011a, 2011b). Therefore the importance of using updated 30-year normal precipitation, in the calculation of SPI time periods, cannot be over emphasized. For continuing with the perception of anomalies under the assumption that climate is stationary even for a future period (i.e. new generations) would disregard climate change. For example, in some places climate change has already altered the precipitation mean conditions, variability and extremes of relevant weather variables, and GCMs project that these changes will continue (Marengo et al., 2016). The inclusion of projected changes in mean precipitation conditions provide more realistic information, although the uncertainty of projected changes in local and regional extremes is still high.

## 5. Conclusions

Drought is recurrent feature of climate variability, apparently, its criterion is increasingly becoming a moving target as projected climate change eventuates. Projections of changes in drought characteristics for 2050 and 2070 periods while accounting for changes in precipitation normal conditions reveal moderate and non-monotonic changes in drought characteristics for Brazil.

The 4-fold projection changes in the probability of drought-year occurrences based on 'static' normal precipitation with values up to 250% relative to 1990, against projections based on the dynamic normal conditions, seem to be unrealistic. In addition, they show a tendency of monotonic increases in the magnitudes of change over time that is not consistent with the precipitation time series.

Based on the '30-year dynamic' normal precipitation conditions, the 13-member GCM ensemble median estimates of changes for 2050 under rcp4.5 and rcp8.5 show: (i) Significant differences between changes associated with rcp4.5 and rcp8.5, and are more noticeable for droughts at long than short timescales in the 2070; (ii) Overall, the results demonstrate more realistic projections of changes in drought characteristics over Brazil than the previous projections mainly based on 'static' normal precipitation conditions. However, the uncertainty of response of droughts to climate change in CMIP5 simulations is still large, regardless of GCMs selection and translation processes undertaken in this study.

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**Table 4**

The 13-GCM member ensemble median changes in the 50th and 90th percentiles of drought areal-extent over Brazil for the 2050 and 2070 periods under rcp4.5 and rcp8.5 scenarios of greenhouse gases emission pathways.

Period	Changes (%) relative to 1990							
	rcp4.5				rcp8.5			
	DTS6		DTS24		DTS6		DTS24	
	50th perc A-extent	90th perc A-extent	50th perc A-extent	90th perc A-extent	50th perc A-extent	90th perc A-extent	50th perc A-extent	90th perc A-extent
2050	−3.00	2.13	0.89	10.56	−0.04	5.61	1.66	5.04
2070	−11.40	−2.98	4.98	0.66	−3.27	1.60	2.00	7.90

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